



Modelling and Analysis of Renewable Energy Integration and Electric Vehicle Impact on Microgrid Performance: A PSO-Based MPPT and ANFIS-Controlled Battery Approach

D. Ravi Kishore | K. Vijay Kumar | B. Kavya Santhoshi | V. Suresh

Department of Electrical and Electronics Engineering, Godavari Institute of Engineering and Technology (Autonomous), Affiliated to JNTUK, Kakinada, Rajahmundry, A.P, India.

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KEYWORDS	ABSTRACT
Maximum Power Point Tracking, Adaptive Neuro-Fuzzy Inference System, Electric Vehicles, Particle Swarm Optimization..	With the pollution levels and greenhouse gas emissions increasing at an alarming rate, this has further accelerated the growth of Electric Vehicles (EVs), which will likely have a transformational impact on the energy landscape in the years to come. As EVs become increasingly integrated into electricity grids, their impact on both voltage profiles and overall grid load distribution rises above statistics from small test fleets. In this study, the microgrid includes a diesel generator and a Photovoltaic (PV) array attached with a wind turbine, while the V2G system is placed near the load. This paper proposes a Photovoltaic (PV) array model using Particle Swarm Optimization (PSO) as a Maximum Power Point Tracking (MPPT) method to maximize solar conversion efficiency. Moreover, it studies battery management via the Adaptive Neuro-Fuzzy Inference System (ANFIS) to maintain the storage and supply of energy from renewables as well as EVs. Hospitals, universities, and EV charging stations are all venues where the microgrid will provide power to meet their various needs. In this paper, an exhaustive evaluation of the performance of microgrid, especially the impact of EV integration, is shown through MATLAB /Simulink and the effect to network stabilization as well as energy management due to EVs' presence

1. INTRODUCTION

The transport sector contributes a large share to the worldwide greenhouse gas emissions; it produces around 25% of all energy related emissions. Electric Vehicles (EVs) is considered a green and zero emissions vehicles, hence emerging as a potential solution to this problem. A number of countries are actively encouraging the adoption of EVs on a mass scale via incentives and legislation in order to make them an entrenched part of the marketplace.[1] Nonetheless, the uptake of electric cars is predicted to put a significant strain on the electricity grid. And if EVs are charged without any regulation, it may result in increased peaks of electricity demand which can cause grid instability such as voltage dips and power losses along transmission lines, but also equipment overloads. Conversely controlled charging and EVs as distributed energy resources, especially through Vehicle-to-Grid (V2G) technology, has good potential. While electric vehicles can suck power from the grid (Grid-to-Vehicle, G2V), V2G lets them reverse that flow and discharge energy back to the grid, which is invaluable for maintaining grid stability, frequency regulation, and peak-load shaving. The addition of renewable energy sources such as solar or wind power to the microgrid along with expanding EV adoption, also makes it that much more promising. This can include a diesel generator, PV array, wind farm and V2G technology which gives a sustainable power supply that is high-quality for hospitals, universities or EV charging stations.[4] According to my little search, EVs are classified into three types: Battery Electric Vehicles (BEVs), Hybrid Electric Vehicles (HEVs) and Fuel Cell Electric Vehicles (FCEVs); all of which help in limiting the need for fossil fuels. Lots of advancements have been done in the recent years to address many of these issues mainly associated with battery life, making EVs look like a viable option over the traditional Internal Combustion Engine (ICE) cars. Challenges of V2G technology The main challenges with the use of V2G technology are how to handle variety in travel patterns and how to schedule charging cycles that minimize battery degradation yet maximize EV fleet efficiency.

2. MAXIMUM POWER POINT TRACKING (MPPT) OF PHOTOVOLTAIC SYSTEM THROUGH PARTICLE SWARM OPTIMIZATION (PSO)

Solar power is about photovoltaic (PV) systems for the purpose of renewable energy generation. Sunlight is converted into electrical power by solar cells. However, we all know that PV systems do not generate power continuously; it is influenced by the radiation and temperature, as well as the condition. Maximizing the PV-system power output at this point brings the highest efficiency, which is known as Maximum Power Point (MPP). MPPT is just an approach to detecting this point, which changes as per the changes in nature. There are many other methods for studying the MPPT, such as Particle Swarm Optimization (PSO), which is a heuristic optimization method inspired by the collective behaviour of birds flocking or fish schooling [6]. The simplicity, rapid convergence, and the capability of avoiding non-linearities as well as dwelling in any local optimum make PSO one of the most efficient ways for MPPT in PV systems [10].

1. Maximum Power Point Tracking (MPPT):

Maximum Power Point Tracking (MPPT): The MPPT is just one of the methods to get the maximum power from any Solar cell, PV module, wind turbine and some kind of energy source. The trick is to make sure your PV system can optimally perform in some different conditions that are ensured none-optimality depending on the environment. A power-voltage (P-V) curve of a photovoltaic module can have only one peak because the Maximum Power Point (MPP) occurs at a single point. Partial shading: Partial shading can cause the power curve to have multiple peaks, and it becomes a challenging task to determine the Maximum Power Point. [3].

2. Particle Swarm Optimization (PSO)

PSO is a stochastic optimization algorithm that simulates the social behaviour of birds flocking and fish schooling in nature. For MPPT, PSO will be used to find the optimum operating point of the PV system where the output power is maximized. How PSO Works:

A swarm of particles, each particle representing a candidate solution, is initialized with random position and velocities in the search space, such as the voltage range of the PV system. Fitness evaluation: Fitness function is calculated for every particle, which in the case

of the MPPT task, is the power delivered by the PV module at that particular operating voltage.

3. Wind Energy: Harnessing the Power of Wind for Renewable Energy Generation

The renewable energy, earlier came into use in the form of wind energy. This is a clean, renewable and environmentally friendly source of energy that could dramatically cut carbon emissions and the reliance on fossil fuels. Wind power is collected by means of wind turbines, which convert the energy inedible wind to mechanical might and further on electrical engine present is. The need for renewable energy sources due to growing threat of climate change further strengthens the case for increase in deployment of wind energy as key component in our global energy mix.[5]

2.1 Wind Energy Conversion Process

To model the wind turbine system, various mathematical formulas and calculations are applied to quantify how much energy one could generate from creating such a mechanical system, as well as its overall efficiency. These consist of wind energy power output, which is followed by how to determine the capacity factor and then the turbine Efficiency.

The following are the most popular mathematical models for wind energy:

1. Wind Power Calculation

$$P = \frac{1}{2} \rho A v^3 \quad \text{---(1)}$$

The wind capacity is the power that can be potentially delivered based on the winds as calculated.:Where: P = Power (W) ρ = Air density (kg/m^3) $\approx 1.225 \text{ kg/m}^3$ at sea level A = Swept area of the turbine (m^2) $A = \pi r^2$, where r is the radius of the turbine blades. v = Wind speed (m/s) It is the kinetic energy of the wind flowing through the blades of a turbine that leads to this formula. Power is proportional to the wind speed cubed.

2 Power Coefficient (C_p)

The wind energy cannot be completely harnessed by the turbine. A wind turbine is rated by its Power Coefficient (C_p), representing the constraints introduced by the Betz Limit, stating that the maximum energy any wind turbine can extract from a fluid stream varies from 59.3% for a rotor with an infinite number of blades to 33.33% for one with only one blade.

$$P_{\text{turbine}} = \frac{1}{2} \rho A v^3 \cdot C_p \quad \text{---(2)}$$

Where: P_{turbine} = Power extracted by the turbine (W) C_p = Power coefficient (usually ranges from 0.3 to 0.5 for conventional wind turbines)

The value of C_p is typically less than 1, and the Betz Limit states that C_p can never exceed 0.593.

3. Energy Output Over Time

To calculate the total energy produced by a wind turbine over a given period, we use the following formula:

$$E = P_{\text{turbine}} \times t \quad \text{---(3)}$$

Where: E = Energy output (Wh or kWh) P_{turbine} = Power extracted by the turbine (W) t = Time (hours) This gives the energy produced by the turbine in kilowatt-hours (kWh) or watt-hours (Wh) over a specified time period.

4. Capacity Factor

The capacity factor (CF) is a key metric that describes the actual energy production of a wind turbine relative to its theoretical maximum output. It is a measure of how effectively a turbine operates over time.

$$CF = \frac{E_{\text{actual}}}{E_{\text{max}}} \times 100 \quad \text{---(4)}$$

Where: E_{actual} = Actual energy output over a period of time (kWh)

E_{max} = Maximum possible energy output if the turbine operated at full capacity all the time (kWh) The capacity factor varies depending on wind conditions, but typical values for onshore wind turbines range from 20% to 40%, while offshore wind turbines may have a higher capacity factor (up to 50%).

5. Tip Speed Ratio (TSR)

The blade tip speed is as a multiple of the wind velocity, which is abbreviated as Tip Speed Ratio (TSR). It is the crucial factor in wind turbine design since it impacts on power efficiency.

$$TSR = \frac{r \cdot \omega}{v} \quad \text{---(5)}$$

Where: r = The turbine blades are the radius of the circle (in m) ω = Angular speed of the rotor (rad/s) v = Wind speed (m/s) Ideally, a TSR for best efficiency on a wind turbine is between 6 and 10, which a higher TS rate can

indicate a more efficient operation under high wind speeds.

6. Wind Turbine Efficiency

Wind turbine efficiency can be defined as the ratio of the wind energy extracted by a wind turbine to the wind energy available in the region where it is installed.

$$\eta = \frac{P_{\text{turbine}}}{P_{\text{wind}}} \times 100 \quad \text{--(6)}$$

Where: η = Efficiency (%) P_{turbine} = Power extracted by the turbine (W)

P_{wind} = Power available in the wind (W) The maximum efficiency is typically limited by the Betz Limit: The maximum efficiency of a wind turbine is limited by the Betz Limit, which says that no wind turbine can capture more than 59.3% of the energy in the wind.

7. Wind Energy Cost Calculations

The Levelized Cost of Energy (LCOE) is a critical economic metric used to assess the cost of generating electricity from wind turbines. It is the price at which energy must be sold for a project to break even and cover the initial investment, operations, and maintenance costs.

The formula for LCOE is: *

$$LCOE = \frac{\sum_{t=1}^N (C_t + O_t)}{\sum_{t=1}^N E_t} \quad \text{--(7)}$$

Where: C_t = Capital costs in year t , O_t = Operating and maintenance costs in year t , E_t = Energy produced in year t , N = Project lifetime.

2.2 Control Process with ANFIS

ANFIS Training:

The ANFIS model is trained using historical data or simulation data, where the system learns to associate the inputs with the desired outputs. The training process adjusts the fuzzy membership functions, improving the system's accuracy in predicting and controlling the charging/discharging actions. The training process involves minimizing a cost function, which measures the error between the predicted and actual battery conditions.

Output: The output of the ANFIS system is a control action that is sent to the Battery Management System to regulate the battery's charging or discharging. The control action can be:

Adjusting the charging current or voltage. Adjusting the load applied to the battery. Deciding when to switch between charging and discharging modes. The fuzzy system can output values like: Charging Current: "High", "Medium", "Low" Discharge Current: "High", "Moderate", "Low" State of Charge (SOC): Maintaining an optimal SOC range.

Application Example: Battery Charging Control Using ANFIS

In a solar PV-based energy storage system, an ANFIS-based battery control system can be used to regulate the charging of batteries from the PV array[8]

3. RESULTS AND DISCUSSION

Power Generation Profile

There are load demands, so the power output of a generator changes during the day, from second to second, by even within seconds, plus there are environmental conditions and the operating cycle of a generator. When we want to carry out a power analysis on a diesel generator or any other generator, one of the many factors involved is the at which it operates (AHAA) during the day, as well as where all its most frequented load profiles the list does not stop there, fuel consumption and efficiency and lastly some environmental conditions can surely have an impact on how much power your generator delivers. overcharging and keeping the SOC at the target range. The ambient temperature.

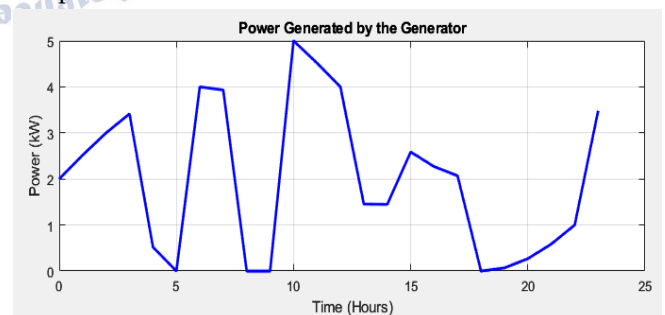


Figure 1. Power is generated by the generator.

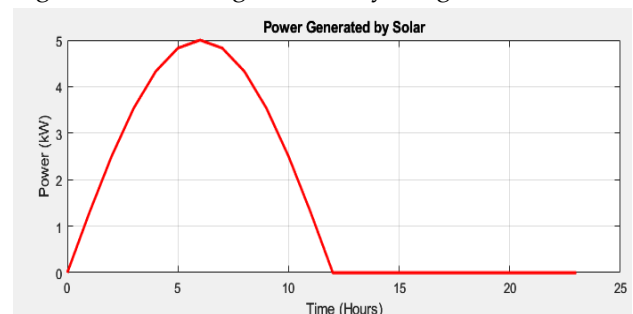


Figure 2. Power is generated by the solar.

Wind Farm

The wind farm generates power proportionate to the speed of the wind. The turbines achieve their rated power output when the wind speeds are above a certain level. If wind speeds exceed this limit, the plant is taken off line until winds subside to within usable limits. Daily energy output of the wind farm inside the microgrid, Figure 3

Wind power plants are increasingly being adopted for microgrids because of the fact that they are renewable and have a relatively simple structure. Wind farms have attributes that differentiate them from traditional types of power generation and make them an attractive renewable energy source for microgrids.

Electric Vehicles (EVs) - Take, for example, electric cars, which can give you the capability of Vehicle to Grid (V2G) that no other solid-based car model can provide; they do have much more advantages. With V2G, EVs can feed power in from the distribution microgrid and help stabilize the grid. Figure 6 shows the amount of power supplied and traded by the EV to its electrified microgrid during the course of each day.[7]

To address these challenges, an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller can be implemented. The ANFIS controller optimizes the charging and discharging cycles of EV batteries based on real-time grid conditions and energy demands. By dynamically adjusting the charging rates and coordinating the load distribution, the ANFIS controller ensures that the microgrid remains balanced, preventing phase imbalances, voltage drops, and power losses. This intelligent control mechanism helps to maintain the overall stability and efficiency of the microgrid even during periods of high EV charging

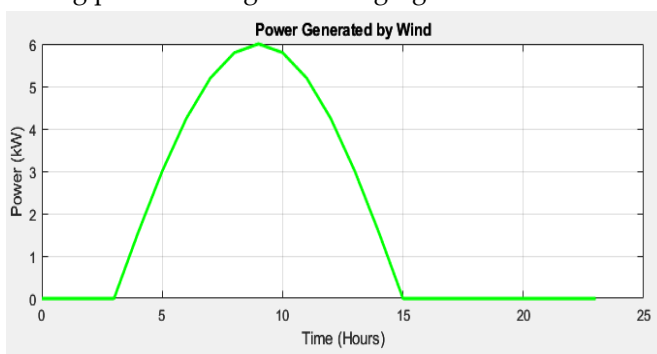


Figure3. Charged and regulated into the microgrid

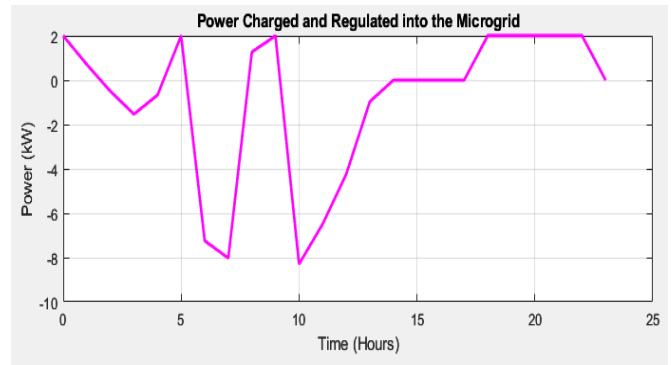


Figure 4. Power is generated by the wind

Neuro-Fuzzy Inference System (ANFIS) is responsible for controlling of battery charge and using the available power to stabilize the grid by providing reserve energy during the transient events. One of the ways ANFIS can increase V2G Systems' own efficiency as an adaptive and intelligent control mechanism that can dynamically optimize distribution and consumption energy storage. This helps in making sure that the present decentralized energy storage systems are easily accessible and managed effectively. Different battery types are available in the market, and ANFIS can improve their performance according to contemporary grid conditions. Figure 5: Simple Example Residential Load – Active power at a Given Power Factor. For the residential load, it is represented by active power being drawn at a certain power factor. ANFIS subtly manipulates the charging and discharging cycles of EV batteries to sync them with the demand of the grid. At any instant, the sum of active power supplied by all DERs determines total power generated by the microgrid, which must be greater than or equal to the load. An ANFIS controller is employed to manage the energy demand along with generation and battery operation in real-time to achieve a balance, as shown in Figure 6.

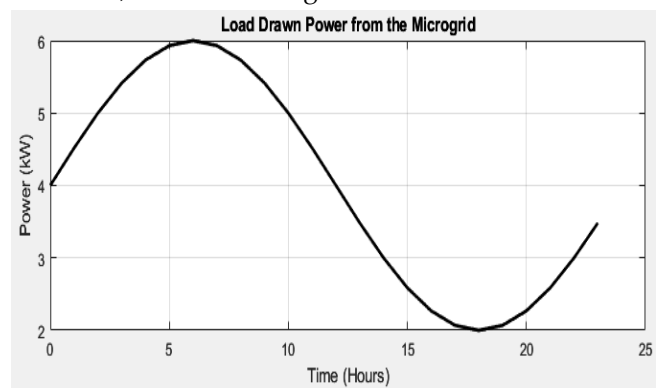


Figure5. Load drawn from the microgrid during

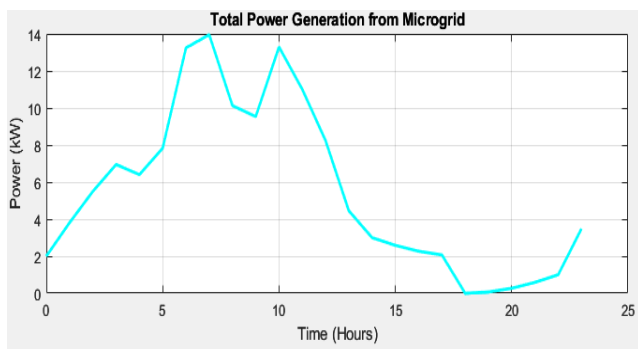


Figure6. Charged and regulated into the microgrid

4. CONCLUSION

A comprehensive study has been conducted for the scenario where Electric Vehicles (EVs) is introduced to bolster renewable capacity contribution, especially in a microgrid context as part of the distributed generation. Proposed microgrid can improve distributed energy generation, utilization, and overall network stability by incorporating solar photovoltaic (PV) arrays, wind farms with vehicle-to-grid (V2G), efficient energy storage controlled by an adaptive neuro-fuzzy inference system (ANFIS.) In this paper, Particle Swarm Optimization (PSO) for Maximum Power Point Tracking (MPPT), is used to maximize solar energy conversion in order to gain a higher efficiency. signalling that the integration of EVs in the microgrid has a clear influence on voltage profiles and load distribution, stressing to take into account effective management strategies and battery limits. This study offers important insights on how microgrid systems, especially in facilities such as hospitals, universities, and EV charging stations, can better respond to the continuously growing need for clean and sustainable energy. In this connection, simulation results from the platform of MATLAB/Simulink. further confirm the feasibility and robustness, and real-world applicability of such systems to stabilize ride, increase performance in operation, aiding an environmentally friendly, low-emission

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

- [1] Beniwal, MKSaini, A Nayyar, BQureshi, and A Aggarwal, "A critical analysis of methodologies for detection and classification of power quality events in smart grid," *Ieee Access* vol. 9, pp. 83507–83534, 2021.
- [2] J. Y. Yong, V. K. Ramachandaramurthy, K. M. Tan and N.M.Ananthan, "A Review on the State-of-the-Art Technologies of Electric Vehicle: Its Impacts and Prospect", *Renew. Sustain. Energy Rev.*, vol. 49, pp. 365–385, Sep. 2015.
- [3] Y. Qi, G. Mai, R. Zhu, and M. Zhang, "EVKG: An interlinked and interoperable electric vehicle knowledge graph for smart transportation system," *Trans. GIS*, vol. 27, no. 4, pp. 949–974, Jun. 2023
- [4] M. H. Nikkhah and M. Samadi, "Evaluating the effect of electric vicle charging station locations in line flows: An intuitive approach," *Proc. 30th Int. Conf. Electr. Eng. (ICEE)*, May 2022, pp. 287–291.
- [5] S. Habib, M. Kamran, and U. Rashid, "Impact analysis of Vehicle-to-Grid technology and charging strategies of electric vehicles on distribution networks-A review," *J Power Sources*, vol. 277, pp. 205–214, Mar. 2015.
- [6] Garcia-Torres, D. G. Vilaplana-Celis, C. Bordons Alonso, P. Roncero-Sanchez and M. A. Ridao-Marquez," Optimal management of microgrids with external agents including battery/fuel cell electric vehicles", *ELSEVIER_CONTROL ENGINEERING PRACTICE* VOL 77 PP 94-105 JANUARY 2018 [Online]. *Smart Grid*, vol. 4, pp. 4299-4308, Jul. 2019. '
- [7] S.-A. Amamra and J. Marco, "Vehicle-to-grid aggregator to support power grid and reduce electric vehicle charging cost," *IEEE Access*, vol. 7, pp. 178528–178538, 2019.
- [8] C. Liu, K. T. CHau, D. Wu and S. Gao, "Opportunities and challenges of vehicle-to-home, vehicle-to-vehicle and vehicle-to-grid technologies," In *IEEE*, vol. 101, Issue 11, pages: 2409-2427, November 2013.
- [9] S. Shahriar, A. R. Al-Ali, A. H. Osman, S. Dhou and M. Nijim, "Machine learning approaches for EV charging behavior: A review," in *IEEE Access*, vol. 8, pp. 168980–168993, 2020.
- [10] K. Ginigeme and Z. Wang, "Distributed Optimal Vehicle-to-Grid Approaches with Consideration of Battery Degradation Cost under Real-Time Pricing," *IEEE Access*, vol. 8, pp. 5225–5235, 2020.
- [11] P. Sinha, K. Paul, S. Deb, and S. Sachan, "Comprehensive review based on the impact of integrating electric vehicle and renewable energy sources to the grid," *Energies*, vol 16, no. 6, pp. 2924, Mar. 2023.
- [12] J. James, J. Lin, A. Y. Lam, and V. O. Li, "Maximizing aggregator profit through energy trading by coordinated electric vehicle charging," in *Proc IEEE Int. Conf. Smart Grid Commun. In: Proceedings of the Seventh IEEE International Conference on Smart Grid Communications (SmartGridComm)*, Sydney, NSW, Australia, 2016; pp. 497–502.
- [13] Y. Vardanyan, FjsonpDocfCallbackRferArr; F. Banis; S. A. Pourmousavi; H. Madsen,Ootl;- @rlet([? IEEE Int. Energy Conf. In *ENERGYCON*, Limassol, Cyprus, Jun. 2018, pp. 1–6. L Z A0044 Intelligent energy management algorithms for EV-charging scheduling with consideration of multiple EV charging modes *Energy.findByIdAndUpdate*
- [14] T. Mao, X. Zhang, B. Zhou, "Intelligent energy management algorithms for EV-charging scheduling with consideration of multiple EV charging modes," *Energies* (2019) 12, no. 2, p. 265, Jan. 2019.